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Bubbles, Fads and Stock Price Volatility Tests: A Partial Evaluation

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ABSTRACT

This is a summary and interpretation of some of the literature on stock price volatility that was stimulated by Leroy and Porter [28] and Shiller [40]. It appears that neither small-sample bias, rational bubbles nor some standard models for expected returns adequately explain stock price volatility. This suggests a role for some nonstandard models for expected returns. One possibility is a "fads" model in which noise trading by naive investors is important. At present, however, there is little direct evidence that such fads play a significant role in stock price determination.

NEARLY SEVEN YEARS HAVE passed since the publication of the original LeRoy and Porter [28] and Shiller [40] volatility tests. The number of papers analyzing or developing volatility tests on stock prices has now grown to the point that a nonspecialist may have trouble getting even a general sense of the current state of the volatility debate. This paper is intended to help such a nonspecialist, by summarizing and interpreting the literature.

Section I summarizes the techniques and conclusions of some volatility tests that assume constant expected returns. Section II considers whether small-sample bias is likely to explain the excess price volatility found in most of the studies summarized in Section I. The presence of near or actual unit-root nonstationarity in stock prices certainly causes substantial small-sample bias in the test in Shiller [40], and quite possibly in other studies that assume stationarity. Subsequent studies that explicitly allow for unit roots find excess volatility that is typically an order of magnitude smaller than for studies that assume stationarity—but they do still tend to find substantial excess volatility. While not much is known on small-sample bias in tests that allow for unit roots, it does not seem that such bias explains the persistent finding of excess volatility. Indeed, I present a little evidence that certain tests that do *not* find excess volatility have poor small-sample power against interesting alternatives.

The rest of the paper proceeds under the tentative conclusion that stock prices are more volatile than can be explained by a standard constant-expected-return model. Section III considers explaining the excess volatility by adding to the usual constant-expected-return stock price an explosive rational bubble (Blanchard and Watson [3], West [52]). For a variety of theoretical and empirical reasons, this does not seem to produce a satisfactory explanation.

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If bubbles are ruled out, so that any deviations from the constant-expected-return stock price are transitory, these deviations will give rise to predictable variations in returns. Section IV considers whether stock price volatility is adequately explained by some standard models for expected returns. The evidence here is somewhat limited, but the answer appears to be no (Campbell and Shiller [7], West [53]). This seems to be true at least in part because such models do not generate sufficient variability in expected returns.

This suggests that it might be useful to consider some nonstandard models for what determines expected returns. Section V interprets "fads" models as arguing that trading by naive investors creates nondiversifiable risk that sophisticated investors must take into account (Campbell and Kyle [5], DeLong et al. [11], Shiller [43]). It follows that an appropriate model for expected returns will reflect such trading. The fads literature is, however, rather new, and has yet to model risk as precisely as have the traditional models discussed in Section IV. There is little direct evidence that trading by naive investors plays a substantial role in stock price determination. Such evidence as there is in favor of fads is largely indirect, and consists of negative verdicts on traditional present-value models. One would prefer a parametric model, so that the model potentially could be rejected because of implausible parameter estimates or painfully large test statistics.

I conclude that the most important direction for future research on stock price volatility is therefore not still more volatility tests, but development of parametric models to explain the excess volatility that some, including me, believe to be reasonably well established. My own sense is that consideration of fads is likely to be productive. But someone skeptical about fads models could reasonably conjecture that any such models will be in as much conflict with the data as are traditional present-value models, and that refinements of these latter models are a more promising avenue for research.

Before turning to a detailed discussion, it is well to remind the reader that this is a partial evaluation of volatility tests, in two senses. First, space constraints preclude detailed discussion of many relevant issues. I give relatively short shrift to some of the topics covered in detail in the survey paper of Gilles and LeRoy [20], which focuses on potential problems with Shiller's [40] test, and of Camerer [4], which discusses in detail how imperfect aggregation of information can lead to seeming excess volatility of stock prices. Second, as a participant in this literature, I am hardly unbiased. While I have attempted to represent all points of view, I have of course emphasized those that I find most compelling.

I. Overview of Empirical Results

Table I summarizes the results of some volatility tests that assume constant ex ante returns. To make this task manageable, I have limited myself to empirical results that in my somewhat arbitrary opinion could be cast in the form V/V^*, where V measures the volatility of the market's forecast of fundamentals, V^* the volatility of the econometrician's measure of fundamentals, and $V/V^* > 1$ indicates excess volatility. This means that while most of the papers cited below

Table I

Volatility Tests, Constant Expected Return

(1) Author	(2) Sample	(3) V/V^*	(4) p-value	(5) unit root?
A. Asymptotically valid under stationarity:				
(1) Blanchard and Watson [3]	annual, 1871–1979	72	.00	no
(2) Kleidon [25]	$T = 100$	25	.05–.50	logarithmic
(3) Leroy and Porter [28]	quarterly, 1955–73	16–148	.01–.50	no
(4) Shiller [40]	annual, 1871–1979, 1928–1979	31–176	n.a.	no
(5) Shiller [45]	$T = 100$	25	.00–.01	logarithmic
B. Asymptotically valid with unit arithmetic roots:				
(6) Campbell and Shiller [6]	annual, 1871–1985	1–67	.00–.50	arithmetic
(7) Mankiw et al. [32]	annual, 1871–1984	0–12	n.a.	arithmetic
(8) West [53]	annual, 1871–1980, 1929–1979	5–10	.00–.01	arithmetic
	$T = 100$	5	.05	arithmetic
	$T = 100$	5	.05	logarithmic
C. Asymptotically valid with unit logarithmic roots:				
(9) Campbell and Shiller [7]	annual, 1871–1986, 1926–1986	2–14	.00	logarithmic
(10) Kleidon [25]	annual, 1926–1979	0–1	.50	logarithmic
(11) Leroy and Parke [27]	annual, 1871–1983	0	n.a.	logarithmic
(12) Shiller [42]	annual, 1871–1979	2	.01	logarithmic

Notes: A column (2) entry of "T = sample size" indicates a Monte Carlo study rather than an empirical point estimate. In column (3), entries were rounded down to zero if $V/V^* < 1$, but otherwise were rounded to the nearest integer. See the text for how V/V^* is calculated for a given entry. Entries in column (4) were rounded as follows: .00 means that the reported p-value is less than .005; .01, between .005 and .01; .05, between .01 and .05; .10, between .05 and .10; .50, greater than .10.

test a number of implications of the model being studied, I will consider only those tests that seem to me to be similar in spirit to the original LeRoy and Porter [28] and Shiller [40] comparison of the variance of a stock price (V) to that of a certain function of dividends (V^*). My sense is that my self-imposed restriction probably selects from the studies cited below the *less* rather than the more striking evidence; the equality tests in LeRoy and Porter [28] and Mankiw et al. [32], for example, yield sharper results than do the inequality tests reported below. Analyses that supply neither new empirical nor Monte Carlo estimates (e.g., Marsh and Merton [33]) are ignored in this section but will be discussed later.

To facilitate the discussion below of whether inappropriate accounting for unit-root nonstationarity explains the results of the volatility tests, the papers in Table I are grouped according to whether the test is asymptotically valid only under stationarity, with a unit arithmetic root (ΔP_t stationary), or with a unit logarithmic root ($\Delta \log(P_t)$ stationary). Listings within each group are alphabetical. In Table I, column (2) gives the sample period. Most of the studies use Shiller's [40] long-term annual data, which splices Cowles Commission data beginning in 1871 to more recent data from the Standard and Poor's Composite

Stock Price Index. For convenience I will refer to this as simply the S&P data. Shiller [40] and West [53] also use the Shiller's modified Dow-Jones. Campbell and Shiller [7] also use the New York Stock Exchange equal- and value-weighted indices. With the exception of LeRoy and Porter, all the studies cited in the Table use annual data, in part to avoid dealing with seasonality in dividends. See the cited papers for additional detail on the data.

Column (3) reports the empirical value of V/V^*, calculated for a given paper as described below. The p-value in column (4) gives the probability of seeing the column (3) value for V/V^*, under the null that the model is equation (4) below and unit roots, if any, take the form indicated in column (5). For Monte Carlo studies, indicated by "T = sample size" in column (2), the V/V^* value is not the median but instead matches an estimated empirical value.

A brief discussion of the models and tests now follows. This may be skipped by readers familiar with this literature. This is intended to suggest the basic ideas involved, but not to spell out the precise details. I will slur over inconsequential differences between the models and tests described below and those in the papers cited (e.g., whether current dividends are known when price is set). Some authors have reported asymptotic p-values for test statistics other than V/V^* (e.g., West [53] reports the p-value for H_0: $V^* - V \geq 0$, for V^* and V defined below). In such cases, I have felt free to associate those p-values with V/V^*, even though the statistic for V/V^* would of course be numerically different. Detailed references to the sources of the entries in Table I may be found in the Appendix.

The constant-expected-return model supposes

$$P_t = b\mathrm{E}(P_{t+1} + D_t \mid I_t), \tag{1}$$

where P_t is a real stock price, b a constant discount rate, $b = 1/(1 + r)$, r is the constant real expected return, $\mathrm{E}(\cdot \mid I_t)$ is mathematical expectation conditional on the market's period-t information set I_t, and D_t is the real dividend on the stock. I_t is assumed to contain, at a minimum, current and past P_t and D_t. Substituting recursively for P_{t+1}, P_{t+2}, etc., and using the law of iterated expectations, gives

$$P_t = \mathrm{E}(\textstyle\sum_0^{n-1} b^{j+1}D_{t+j} + b^n P_{t+n} \mid I_t) \equiv \mathrm{E}(P^*_{t,n} \mid I_t). \tag{2}$$

Suppose that the terminal condition

$$\lim_{n\to\infty}\mathrm{E}(b^n P_{t+n} \mid I_t) = 0 \tag{3}$$

holds (this rules out rational bubbles, as explained below). Then (2) implies

$$P_t = \mathrm{E}(\textstyle\sum_0^{\infty} b^{j+1}D_{t+j} \mid I_t) \equiv \mathrm{E}(P^*_t \mid I_t), \tag{4}$$

where P^*_t is used rather than $P^*_{t,\infty}$ to match Shiller [40]. Since P_t is the conditional expectation of P^*_t,

$$\mathrm{var}(P_t)/\mathrm{var}(P^*_t) \leq 1, \tag{5}$$

if the unconditional variances exist. LeRoy and Porter [28] and Shiller [40] estimate (5), using different techniques to calculate the ratio. Kleidon [25] and

Shiller [45] use Monte Carlo methods to determine the finite-sample behavior of (5) when $\log(D_t)$ follows a random walk and I_t consists solely of lagged dividends. These studies are summarized in lines (2) to (5) of Table I, with V/V^* an estimate of the left-hand side of (5).

The Blanchard and Watson [3] test, in line (1), compares variances of innovations rather than levels. Let $H_t \equiv \{D_t, D_{t-1}, \cdots\}$ be the information set determined by current and lagged dividends; H_t is a subset of I_t. Let $P_{tH} \equiv \mathrm{E}(\sum_0^\infty b^{j+1}D_{t+j} \mid H_t) \equiv \mathrm{E}(P_t^* \mid H_t)$. Then since more information tends to lead to more precise forecasts (West [53]),

$$\{\mathrm{E}[P_t - \mathrm{E}(P_t \mid I_{t-1})]^2/\mathrm{E}[P_{tH} - \mathrm{E}(P_{tH} \mid H_{t-1})]^2\} \leq 1. \tag{6}$$

The left-hand side of (6), which Blanchard and Watson [3] calculate assuming stationarity of dividends, is reported as V/V^* in line 1.

One of the major problems of the initial volatility tests, emphasized in particular by Kleidon [25] and Marsh and Merton [33], was of course the assumption that variables do not have unit roots. Lines (6) to (8) of Table I summarize some tests that are appropriate if the nonstationarity results from a unit arithmetic root. In such a case, the model (4) implies that P_t and D_t are cointegrated (Engle and Granger [13]), and $P_t - b(1-b)^{-1}D_t$ is stationary (Campbell and Shiller [6]). Basically, a unit arithmetic root causes a linear (but not exponential) stochastic trend in dividends and prices, so subtracting a suitable multiple of D_t from P_t removes this linear trend in P_t and leaves a stationary random variable. Mankiw et al. [32] show that as a result

$$\{\mathrm{E}[P_t - b(1-b)^{-1}D_t]^2/\mathrm{E}[P_{t,n}^* - b(1-b)^{-1}D_t]^2\} \leq 1 \tag{7}$$

for any finite n, with $P_{t,n}^*$ defined in (2). The V/V^* reported in line (7) results when $n = T - t$, T the last period in the sample.

Campbell and Shiller [6] (line (8)) calculate statistics similar to (6) and (7), expanding H_t to include lagged P_t and D_t. West [53] calculates (6), with H_t defined as in Blanchard and Watson [3] to consist of just lagged dividends, but allows for unit arithmetic roots.

Lines (9) to (12) in Table I report studies that have accounted for nonstationarity by allowing for unit logarithmic roots. Kleidon [25] and Shiller [42] both assume that $\log(D_t)$ follows a random walk, with I_t consisting of only lagged dividends. The model implies that P_t is proportional to D_t, so that

$$\mathrm{var}(P_t/P_{t-1})/\mathrm{var}(D_t/D_{t-1}) = 1. \tag{8}$$

Kleidon notes that the model (4) also implies that for finite n

$$\{\mathrm{var}(P_{t+n}/P_t)/\mathrm{var}(P_{t+n}^*/P_t)\} \leq 1. \tag{9}$$

Estimates of the ratios in (8) and (9) are reported in lines (12) and (10).

LeRoy and Parke [27] also assume that $\log(D_t)$ follows a random walk. By the logic used to develop (5) above, the model (4) implies

$$\{\mathrm{var}(P_t/D_t)/\mathrm{var}(P_t^*/D_t)\} \leq 1. \tag{10}$$

Line (11) reports this ratio, calculated assuming that P_t/D_t follows an AR(1) process.

Campbell and Shiller [7] work with a linearized logarithmic version of (4), assuming stationarity of the log dividend price ratio and log differences of dividends and prices. Line (9) reports estimates of

$$\mathrm{var}[\log(D_t/P_t)]/\mathrm{var}\{[\log(D_t/P_t)]_H\}, \tag{11}$$

where $\log[(D_t/P_t)]_H$ is the variance of the log dividend price ratio when the ratio is calculated as a forecast from an information set H_t consisting of lagged $\log(D_t/P_t)$ and $\Delta \log(D_t)$.

II. Small-Sample Bias

The initial tests, in lines (1), (3) and (4) of Table I, found extreme excess volatility, with the variance of stock prices or their innovations exceeding a theoretical upper bound by orders of magnitude. The statistical significance of the excess volatility was, however, unclear. For example, LeRoy and Porter [28], using the asymptotic distribution, found a violation significant at the five percent level in only one of their four data sets. As is evident from a glance at the estimates of V/V^* for lines (6) on, allowing for unit roots results in considerably smaller estimates of excess volatility. It seems that these initial tests tend to find spuriously large estimates, at least if unit roots are present.

For the Shiller [40] technique for calculating $V/V^* \equiv \mathrm{var}(P_t)/\mathrm{var}(P_t^*)$, reasons for this are developed in Flavin [16], Kleidon [23, 25] and Mankiw et al. [32]. Assume first that P_t and D_t are stationary, so that the population variances of P_t and P_t^* exist. Even though V/V^* can be estimated consistently, Shiller's [40] procedure tends to produce finite-sample estimates that are spuriously high, with the bias likely to be quite pronounced for the relevant sample sizes. Kleidon [23] (pp. 20–21), for example, reports a simulation with a sample size of 100 in which the population value of V/V^* is .81 but the mean estimated value is 2.2. The Marsh and Merton [33] nonstationary example in which the sample estimate $\mathrm{var}(P_t)/\mathrm{var}(P_t^*)$ is greater than one with probability one, for any size sample, might be interpreted as simply a nonstationary limiting case of the biases noted by Flavin [16] and Kleidon [23] (Mankiw et al. [32]).[1]

While the logic of Flavin [16] and Kleidon [23] does not apply directly to the Blanchard and Watson [3] or LeRoy and Porter [28] tests, the dramatic fall in V/V^* when unit roots are allowed suggests that similar arguments are likely to be relevant for those tests. Indeed, the Monte Carlo simulations in Mattey and Meese [35] indicate that the Blanchard and Watson [3] procedure will tend to spuriously find $V/V^* > 1$ if unit roots are present but, as in Blanchard and Watson [3] (but not West [53]), are not imposed. Similarly, Gilles and LeRoy [20] (p. 64), seem to concede that biases similar to those in Shiller [40] are probably present in LeRoy and Porter [28].

This leaves open the question of whether these biases are so large as to explain the entire excess of V over V^* reported in the various tests in Table I. Whether they even totally explain the Shiller [40] results is debatable. Shiller [45] argues that Kleidon's simulation results (line (2)) are very sensitive to the assumed

[1] See Gilles and LeRoy [20] for an excellent exposition.

dividend/price ratio. Kleidon allows a range for this ratio of about 1.5 percent (p-value of $V/V^* \approx .50$) to about 4 percent (p-value $\approx .05$). If the empirical mean dividend/price ratio of about 5 percent is used, the p-value suggested by Kleidon's simulation falls to .01 (line (5)).

While another iteration of the Kleidon-Shiller debate may well suggest that the p-value of .01 is too low, it seems to me unlikely that small-sample biases will suffice to overturn the conclusion that stock prices move more relative to dividends than is consistent with the model (4). I conclude this for two reasons. First, while there is some conflict among the papers summarized in Table I, there often are differences in assumptions and approach that suggest why some tests find excess volatility while others do not. These differences usually seem to me to argue for the plausibility of the tests that find excess volatility. Specifically, the "1" and "0" entries in rows (6) and (7) tend to result when expected returns of less than 4 percent are assumed. Expected returns closer to the actual sample mean of about 8 percent result in the larger, and statistically more significant, figures in these rows. More importantly, as documented below, the Kleidon (line (10)) and LeRoy and Parke (line (11)) tests, which stand out from the other entries in the Table for finding little or no excess volatility, appear to have poor power against a Shiller [43] "fads" alternative (see Gilles and LeRoy [20] (p. 45)). Since it is just such an alternative that has been proposed as an explanation of the results of other volatility tests (Shiller [43]), the Kleidon (line (10)) and LeRoy and Parke (line (11)) results are not persuasive evidence that the results of other tests are misleading.

The second reason I think it unlikely that small-sample biases will overturn the finding of excess volatility is that the other tests in Table I that allow for unit roots do tend to find violations of the relevant variance bounds. While these violations typically are an order of magnitude smaller than those of the initial tests, they still are numerically large. Since these tests directly allow the (near or actual) nonstationarity that probably is central to the small-sample problems with papers in panel A, there does not seem to me to be a reason to suppose any particular bias. In fact, while there is of course some small-sample bias in these tests (Mattey and Meese [35], West [51, 53]), the evidence on this does not suggest that such bias explains the excess volatility that those tests tend to find. See the entries for West [53] in Table I.

The rest of this section contains a small study of the power of the Kleidon (line (10)) and LeRoy and Parke (line (11)) tests against a Shiller [43] "fads" alternative, or, more generally, any alternative that generates slowly decaying deviations of stock prices from the constant-expected-return price determined by (4). Suppose that

$$\log(D_t) = \mu + \log(D_{t-1}) + \varepsilon_t, \tag{12a}$$

$$\log(P_t) = \tau + \log(D_t) + a_t, \tag{12b}$$

$$a_t = \phi a_{t-1} + v_t, \tag{12c}$$

where

$$|\phi| < 1, \quad \varepsilon_t \sim \mathrm{N}(0, \sigma_\varepsilon^2), \quad v_t \sim \mathrm{N}(0, \sigma_v^2), \quad \mathrm{E}\varepsilon_t v_s = 0 \quad \text{for all } t, s.$$

Equation (12a) says that dividends follow a logarithmic random walk, as in Kleidon [25] and LeRoy and Parke [27]. Equations (12b) and (12c) say that the mean log price/dividend ratio τ is perturbed by the stationary AR(1) random variable a_t. The Kleidon [25] setup is a special case of (12) with $a_t \equiv 0$. In the spirit of O'Brien [37], Shiller [43] and Summers [48], one can interpret a_t as a "fad" that drives the stock price away from the value that would result if the data were generated by a model consisting of (4) and (12a).[2]

The S&P data (1871–1985) were used to calculate point estimates of the parameters in (12). The numbers at the foot of Table II result when μ and σ_ε^2 were set to the mean and sample variance of $\Delta \log(D_t)$, τ to the sample mean of $\log(P_t) - \log(D_t)$, $\sigma_a^2 \equiv \text{var}(a_t)$ to the sample variance of $\log(P_t) - \log(D_t)$, ϕ to the sample estimate of $\text{cov}(a_t, a_{t-1})/\sigma_a^2$ and $\sigma_v^2 \equiv (1 - \phi^2)\sigma_a^2$. There are several ways to emphasize that with these parameter estimates, the data generated by (12) are rather different from those generated by a model with constant expected returns and a lognormal random-walk dividend process. First, a shock to a_t that pushes $\log(P_t) - \log(D_t)$ from its mean has a half life of nearly four years ($\phi^4 = .83^4 = .48$). In the sense suggested by Summers [48], this can be argued to be a significant deviation from the constant dividend/price ratio predicted by Kleidon's [25] model. Second, more than half (57 percent, to be exact) of the implied variance of $\Delta \log(P_t)$ is due to shocks to a_t rather than to $\log(D_t)$. Third, the implied standard deviation of the one-period expected return $E[(P_{t+1} + D_t)/P_t \mid I_t]$ is quite substantial, about .05.[3] (The implied unconditional mean return is about 1.08.) For any or all of these reasons, one would hope that a volatility test would distinguish between data generated by (12) on the one hand and (4) and (12a) on the other.

Consider first the LeRoy and Parke test. Computing $\text{var}(P_t/D_t)/\text{var}(P_t^*/D_t)$ requires estimates of just four moments: the mean ex post return, the variance of P_t/D_t and the mean and variance of D_t/D_{t-1} (LeRoy and Parke [27]). But with the parameters listed at the bottom of Table II, data generated by (12) will imply essentially the V/V^* computed by the LeRoy and Parke [27] test, since such data imply essentially these four sample moments. See Table II, panel A. A finding of $V/V^* < 1$ using the LeRoy and Parke [27] test therefore does not in general distinguish the model (4) from the alternative (12).[4]

[2] As emphasized in Section V below, other interpretations are possible. To prevent misunderstanding, I should note that I am not proposing to take (12) as a serious model of stock prices, or even as an adequate characterization of the S&P data: Table 4a in Campbell and Shiller [7] indicates that the assumption that $\Delta \log(D_t)$ and $\log(P_t) - \log(D_t)$ are independent is false. I am merely using (12) to get a quick idea of whether the LeRoy and Parke [27] and Kleidon [25] tests have power against the alternative that there are slow-moving divergences of stock prices from a constant-expected-return fundamental value.

[3] Sketch of algebra: Let I_t consist of past ε_t and v_t. Since P_{t+1}/P_t and D_t/P_t are lognormal, and a_t and $\log(P_t) - \log(D_t)$ are independent, it is straightforward to show that $E[(P_{t+1} + D_t)/P_t \mid I_t] = \exp[\mu + (\phi - 1)a_t + .5(\sigma_\varepsilon^2 + \sigma_v^2)] + \exp[-\tau - a_t]$. The expected return is thus the sum of two lognormal random variables, and one can grind through standard formulas to compute its variance.

[4] My estimate of V/V^* is considerably higher than that of LeRoy and Parke [27], even though data are quite similar. This is basically because the LeRoy and Parke method of calculating $\text{var}(P_t^*/D_t)$ is very sensitive to the estimated value of the following: [mean expected return]$^{-1}$ $\times$ [mean value of D_{t+1}/D_t]. They compute this to be .9548, I get .9427. Were I to use the .9548 figure, V/V^* would fall from .63 to .38, much closer to LeRoy and Parke's estimate of .29.

Table II

Power Against Mean-Reverting Fad

A. Leroy and Parke [27]

	Estimate from S&P	Estimate Implied by Alternative
V/V^*	.63	.63

B. Kleidon [25]

n	Estimate of V/V^* from S&P	Monte Carlo Estimates	
		Median	Prob $V/V^* > 1$
1	.34	.40	.006
2	.69	.77	.303
5	1.66	1.43	.781
10	4.18	1.90	.920

The alternative data-generating process is (12), with: $\mu = .012$, $\sigma_\epsilon = .1244$, $\tau = 3.0$, $\phi = .83$, $\sigma_v = .1347$. One thousand samples were drawn to generate the Monte Carlo estimates in panel B. Additional details are in the text.

Evaluation of the power of the Kleidon [25] test seems to require a Monte Carlo experiment. The simulation generated 1000 samples of size 115, with the presample values of $\log(P_t)$ and $\log(D_t)$ matched to those of the S&P data in 1871, and the presample value of a_t drawn from its unconditional distribution (with a different draw for each simulation). P_t^* was generated recursively, as in Kleidon [25]. The sample estimates of $\text{var}(P_{t+n}/P_t)$ and $\text{var}(P_{t+n}^*/P_t)$ were calculated in the usual way. As stated in Table I, panel B, the median estimates of $\text{var}(P_{t+n}/P_t)/\text{var}(P_{t+n}^*/P_t) \equiv V/V^*$ were less than 1 for $n = 1, 2$, more for $n = 5, 10$. The question is whether the small values for $n = 1$ and 2 are comforting evidence concerning a model consisting of (4) and (12a). The answer appears to be no. In the Monte Carlo simulations for $n = 1$, for example, only 6 of the 1000 samples produced a V/V^* greater than 1. It appears, then, that Kleidon's [25] test, like LeRoy's and Parke's [27], has poor power against this alternative.[5]

I certainly do not consider this a definitive statement on the power of the various tests in Table I, and fully agree with LeRoy and Parke [27] that additional study of the power of volatility tests is of great interest. Nor do I consider the question of small-sample bias completely resolved. Nonetheless, for the reasons summarized above, it seems unlikely to me that small-sample bias provides the bulk of the explanation for the excess volatility reported in Table I.[6]

[5] My estimates of V/V^* are notably bigger then Kleidon's [25] for $n = 5, 10$. Two minor reasons are choice of discount rate (I use the inverse of the mean ex post return, Kleidon tries various imposed values) and sample period. The major reason is that Kleidon calculates $\text{var}(P_{t+n}/P_t)$ and $\text{var}(P_{t+n}^*/P_t)$ by taking the sum of squared deviations not around the respective sample means but, for both, around an estimate of $E(P_{t+n}/P_t)$. If I had mimicked his procedure, the Table II value of V/V^* for $n = 10$, for example, would be 1.80 rather than 4.18. Because the sample means of P_{t+10}/P_t and P_{t+10}^*/P_t are rather different, Kleidon's technique sharply raises the estimate of $\text{var}(P_{t+10}^*/P_t)$ and thus sharply lowers the estimate of V/V^*. Although Kleidon's technique is appropriate under his null, it clearly results in substantial bias under the present alternative.

[6] I should note that the Marsh and Merton [33] dividend-smoothing argument seems to me to be one of small-sample bias induced by inappropriate treatment of unit roots, as suggested above. Marsh and Merton [33] (p. 485), however, seem to suggest that a desire of managers to smooth dividends by itself invalidates volatility comparisons. This is not correct. A key to the validity of the variance-bounds methodology is a stable set of decision rules by market participants, and a sample large

III. Rational Bubbles

Stochastic difference equations such as (1) have a multiplicity of solutions. The solution (4) is unique provided that the terminal condition (3) holds. But if not, there are an infinity of solutions

$$P_t = \mathrm{E}(\sum b^{j+1} D_{t+j} \mid I_t) + C_t$$
$$\equiv P_t^f + C_t. \tag{13}$$

C_t is any variable that satisfies $\mathrm{E}(C_t \mid I_{t-1}) = b^{-1}C_{t-1} \equiv (1 + r)C_{t-1}$, i.e., $C_t = (1 + r)C_{t-1} + V_t$, $\mathrm{E}(V_t \mid I_{t-1}) = 0$. C_t is by definition a rational bubble, an otherwise extraneous event that affects stock prices because everyone expects it to do so.[7] Since the solution (13) satisfies the first-order condition (1), expected returns are constant and there are no arbitrage possibilities. (Rational bubbles are possible with time-varying expected returns. See Flood and Hodrick [17]. I use a constant-expected-return model for simplicity.) The "f" superscript on P_t^f is present because P_t^f depends only on fundamentals.

Blanchard and Watson [3] note that it is possible to have bubbles that grow and pop. The following example of a strictly positive bubble is from West [52]:

$$C_t = \begin{array}{ll} (C_{t-1} - C^*)/\pi b & \text{with probability } \pi \\ C^*/[(1 - \pi)b] & \text{with probability } 1 - \pi \end{array} \tag{14}$$

where $0 < \pi < 1$, $C^* > 0$.

The bubble bursts with probability $1 - \pi$, and has an expected duration of $(1 - \pi)^{-1}$. While the bubble floats it grows at rate $(b\pi)^{-1} = (1 + r)/\pi > 1 + r$: investors receive an extraordinary return to compensate them for the capital loss that would have occurred had the bubble burst. Whether or not the bubble bursts can depend on fundamentals (e.g., $\pi = 1/2$, with the bubble bursting if there is bad news about budget deficits). Alternatively, whether the bubble bursts or not can depend on extraneous "sunspots." It is possible to have a composite bubble, consisting of a linear combination of bubbles like (14), with each (14) bubble having its own π and C^*. Also, π can vary over time (West [52]).

Rational bubbles therefore seem consistent with the recent (1987) pattern of extraordinary stock price increases followed by a dramatic collapse. Rational bubbles also seem a potential rationalization of excess-volatility tests. Even if the bubble is uncorrelated with fundamentals, stock prices move more than the model (4) predicts; if this correlation is positive, so that the market overreacts to news about fundamentals (Shiller [43], DeBondt and Thaler [9]), excessive stock price movements are even easier to rationalize. Moreover, this can be done

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enough for the data to accurately reflect the functioning of those rules. See Kleidon [23, 25]. Note that if this key condition is not met, any statistical inference on the joint dynamics of the dividend process, including that in Marsh and Merton [34], is not valid. See Shiller [41] on the related issue of biases that might result when market participants anticipate events that never occurred.

[7] It should be emphasized that, throughout this paper, the term "bubble" refers to the explosive process C_t. By contrast, many authors (e.g., Ackley [2]) use bubbles to refer to any deviation from fundamentals induced by speculation.

with small or even no variations in ex ante returns. The rational-bubble explanation was one that I favored in West [52] and in the initial version of West [53] (which, in fact, was initially titled "Speculative Bubbles and Stock Price Volatility"). I no longer find this interpretation particularly appealing. I will explain this by first reviewing the theoretical literature on bubbles, and then discussing some empirical results.

One immediate theoretical restriction on rational bubbles is that they cannot be negative. If $C_t < 0$ and the stock price is lower than its fundamental, the possibility of an extraordinary capital gain when the bubble bursts must be compensated for by a potential capital loss if the bubble continues to float downward. Since stock prices must be nonnegative, there will be, for any bubble process, a low enough stock price that precludes any further capital loss. Since such a stock price is inconsistent with a bubble, so, too, is any higher stock price that can lead to such a low stock price. By a backwards recursion, there cannot be a negative bubble on a stock, because any such bubble leads to an infeasible price with nonzero probability.

Are positive bubbles similarly inconsistent with rationality? In models where agents have infinite horizons, the answer appears to be yes (Tirole [49]).[8] Any agent who sells a stock at a price higher than its fundamental can exit the market, leaving negative present value for whomever buys it. Bubbles are ruled out when agents have infinite horizons even if traders have differential information and if short sales are prohibited (Tirole [49]).

Positive bubbles are not, however, ruled out in models with finite-horizon agents. Tirole [50] studies this in a nonstochastic, perfect foresight, overlapping-generations model. Each generation will be willing to pay more than fundamental value for an asset, provided the succeeding generation is similarly willing. It is necessary that the bubble not inflate the stock price so fast that stock market wealth ends up exceeding GNP (to take an extreme example). Otherwise, a backwards recursion will rule out bubbles. In Tirole's [50] model, this means that the rate of growth of the economy must be greater than the return on the stock. In such a case, the steady-state per capita bubble may be positive.

While I am not aware of a stochastic version of Tirole's model, intuition suggests (to me, at least) that such a generalization can be accomplished. Some unpleasant issues would, however, have to be handled. Diba and Grossman [12] note that if there ever is a bubble, it would have to be present from the first day of trading: $E(C_t \mid I_{t-1}) = (1 + r)C_{t-1}$ and C_t nonnegative means that if $C_{t-1} = 0$, then $C_t = 0$ with probability one. Merton [36] notes that there must be some mechanism to limit managerial issues of new stock.

More fundamentally, one must ask how reasonable is Tirole's necessary condition that the mean growth rate of the economy be greater than the mean return on the stock price (assuming, again, that this is a necessary condition in a stochastic version of Tirole's model).[9] The mean annual real ex post return on S&P data 1871–1986 is about 8 percent; the mean growth rate of real GNP is

[8] But see Gilles and LeRoy [19], which apparently concludes that bubbles can in principle exist in such models.

[9] See Abel et al. [1] for a discussion of conditions that rule out bubbles in a stochastic environment.

about 3 percent.[10] In the case of a bursting bubble such as in (14), moreover, the relevant comparison is probably between one plus the growth rate and $(1 + r)/\pi > 1 + r$ rather than $1 + r$: one presumably must insure zero probability that the stock price exceeds the value of national output. While taxes and so forth muddy the issue, the excess of the mean ex post return on aggregate stock price indices over the mean growth rate of the U.S. economy does not suggest that Tirole's necessary condition will apply. See Abel et al. [1].

Is the seeming excess volatility of stock prices nonetheless strongly suggestive of rational bubbles? There are several reasons why the answer seems to me to be no. First, Flood and Hodrick [18] argue that at least certain stock market tests, including Mankiw et al. [32], implicitly allow bubbles under the null.[11] Some tests for finite-maturity bonds also find some evidence of excess volatility (e.g., Singleton [46]), which, if true, cannot be due to bubbles; there cannot be a bubble on the final date when the bond matures, and therefore by a backwards recursion there cannot be a bubble at any earlier date. One would like to have a common explanation for the excess volatility that seems to be found in these various tests applied to various assets. Second, as discussed in West [52], while my tests are perfectly capable of finding something that looks roughly like a bubble, they are probably not able to discriminate between a bubble and "noise" that is almost but not quite a bubble: $E(C_t \mid I_{t-1}) = \phi C_{t-1}$, $\phi =$ (say) .99 instead of $\phi = (1 + r) \approx 1.08$. Third, bubbles suggest that stock prices should grow at a rapid rate. If dividends grow more slowly than the rate of return (an assumption implicitly made when $E(\sum b^j D_{t+j} \mid I_t)$ was assumed to be well defined in (13)), the dividend/price ratio should fall and capital gains should take an increasingly large share of ex post returns. But for the S&P data, 1871–1986, this does not seem to be the case. The mean ex post return in the first half of the sample, 1872–1928, is 8.6 percent, with a mean dividend/price ratio of .053; in the second half of the sample the figures are 8.3 percent and .051.[12]

In sum, theory for rational bubbles is still at a preliminary stage. But the theory so far developed suggests conditions for bubbles that are too stringent to make bubbles particularly attractive: the growth rate of the economy must be greater than the return on the stock; any asset with a bubble must have always had a positive bubble; factors other than bubbles must explain any excess volatility on finitely lived assets and perhaps some of the excess volatility on stock prices as well. In addition, the evidence for explosive bubbles in West [52] is at best suggestive and consistent as well with deviations from fundamentals being borderline stationary.

[10] I computed this using the figures for GNP in 1875–1985 in Gordon [21] and for GNP in 1986 in the October 1987 issue of the Federal Reserve Bank of St. Louis's *National Economic Trends*.

[11] The Mankiw et al. [32] test is, however, likely to be unreliable in the presence of bubbles, even though these are allowed under the null. Confidence intervals will be large: in the presence of bubbles, the variance of the Mankiw et al. [32] estimates is blowing up, for exactly the reasons the variance blows up in the presence of a logarithmic random walk (Merton [36]).

[12] As usual, there is also potentially a peso problem, where anticipations of a never-realized shift in the dividend process can look like a bubble that grows and pops. See Flood and Hodrick [17], Obstfeld and Rogoff [38], and Smith [47].

IV. Variations in Expected Returns

A natural candidate to explain any excess price volatility is movements in expected returns. This was of course among the explanations proposed in some of the first published comments on volatility tests (Long [30]), and has been argued more recently by Flood et al. [18]. Indeed, the model (4), and therefore the variance bounds that follow from it, requires only the terminal condition (3) and a constant expected return. So if, in population, there is excess volatility, and bubbles are ruled out, with deviations from the constant-expected-return stock price fundamental being transitory it follows that mathematically expected returns are varying. See Campbell and Shiller [8] and Flood et al. [18] for interpretations of volatility tests as especially powerful tests of the null of constant expected returns.

A general form for a model with time-varying expected returns is

$$P_t = \mathrm{E}[\textstyle\sum_{j=0}^{\infty} (\prod_{i=0}^{j} {}_{t+i}r_{t+i+1}) D_{t+j} \mid I_t], \tag{15}$$

where ${}_{t+i}r_{t+i+1}$ is the one-period return expected by the market in period $t + i$ (e.g., ${}_t r_{t+1} \equiv \mathrm{E}[(P_{t+1} + D_t)/P_t \mid I_t]$). What sorts of movements in expected returns must be occurring to explain the results in Table I?

First of all, these movements apparently must be large. Using a linearized version of (15), but modeling expected returns nonparametrically, Shiller [40] finds that annual real expected returns would have to have a standard deviation of more than 4 percent. West [53] and Poterba and Summers [39], also using linearized models but allowing for unit roots, conclude that even larger movements in expected returns are necessary to rationalize stock price movements.[13] These authors seem to consider this a wider range than is typically considered reasonable.

Second, two volatility tests that allow for time-varying expected returns do not suggest that the excess volatility in Table I is adequately explained by some standard intertemporal models. One study, Campbell and Shiller [7], uses a linearized version of (15) to compute (11), allowing for three different models for expected returns: the return on short debt plus a constant; the consumption-based asset-pricing model (Lucas [31]) with constant relative risk aversion, $U(C_t) = C_t^{-\alpha}$; and the return on short debt plus a term that depends on the conditional variances of stock returns. The information set used to calculate equation (11)'s $\mathrm{var}\{[\log(D_t/P_t)]_H\}$ consists of lagged $\log(D_t/P_t)$, $\Delta \log(D_t)$ and lagged ex post returns.

A second study, West [53], uses (15) with expected returns determined by the consumption-based asset-pricing model, with constant relative risk aversion and a coefficient of relative risk aversion less than two. This model implies a condition like (6), with P_t and D_t replaced by $\tilde{P}_t \equiv P_t C_t^{-\alpha}$ and $\tilde{D}_t \equiv D_t C_t^{-\alpha}$, and $H_t \equiv \{\tilde{D}_t, \tilde{D}_{t-1}, \cdots\}$.

The results of the two studies are reported in Table III. Neither finds that the assumed model of expected returns adequately rationalizes stock price move-

[13] Unlike Shiller [40], however, neither West [53] nor Poterba and Summers [39] give any evidence on the accuracy of their linearizations. West's [53] in particular is unlikely to be very reasonable in the presence of unit roots.

Table III

Volatility Tests, Varying Expected Return

(1) Author	(2) Sample	(3) V/V^*	(4) p-value	(5) return model
(1) Campbell and Shiller [7]	annual, 1889–1986,	2–8	.00	constant premium
	1926–1986	1–8	.00–.50	consumption
		2–12	.00–.50	return volatility
(2) West [52]	annual, 1889–1978	5–30	n.a.	consumption

Notes: See notes to Table I. As explained in the text, in column (5), "constant premium" means expected stock returns have a constant premium over that on short debt; "consumption" means expected stock returns are determined by the consumption-based asset-pricing model; "return volatility" means expected stock returns have a premium over that on short debt, with the premium dependent on the volatility of stock returns.

ments. Campbell and Shiller [8] further find little theoretically plausible connection between stock prices and their measures of expected returns and suggest (p. 35) that the smaller and less significant estimates of V/V^* are found in specifications that seem to pick up certain spurious correlations. It should be noted that both papers allow for unit roots, so that there is no obvious reason to believe that small-sample bias explains the excess volatility.

Now, one could argue about the accuracy of the linearizations used, or about the validity of the models of expected returns assumed in the parametric tests in Table III, or about how well official consumption data capture the utility flows really necessary to test the consumption-based asset-pricing model. There are many nontrivial problems associated with the test just described. But the evidence to date does not suggest that traditional models of return determination successfully explain the seeming excess volatility of stock prices, even in conjunction with small-sample bias.

V. Fads

The tentative conclusion that neither rational bubbles nor traditional models of return determination can explain stock price volatility suggests that a nontraditional model for return determination might be required. In "fads" interpretations of the volatility tests, noise trading by naive investors plays a significant role in stock price determination. Shiller [43] and DeBondt and Thaler [9] argue that psychological and sociological evidence is consistent with individuals following "irrational" trading rules, overreacting to news. Potentially, this both generates wide variations in expected returns and renders inadequate traditional models for return determination.

One simple way to think through the possible effects of fads is to add a factor due to noise trading to the level or log of what would be the fundamental price if expected returns were constant (Campbell and Kyle [5], Poterba and Summers [39], O'Brien [37], Shiller [43]). Equation (12) is a simple example of this (though to capture investor overreaction one might want the innovation in a_t to be positively correlated with the innovation in $\log(D_t)$). Recall that the equation (12) example, with parameters matched to the S&P estimates, does indeed generate wide swings in expected returns, with a standard deviation of about .05. Also, one could of course capture the 1987 runup and then collapse of stock prices by allowing a stationary version of the explosive bubble (14). For example, if $a_t = (\phi/\pi)a_{t-1} + v_t$ with probability π, $a_t = v_t$ with probability $(1 - \pi)$, $0 < \phi$, $\pi < 1$, and $E(v_t \mid I_{t-1}) = 0$, then $E(a_t \mid I_{t-1}) = \phi a_{t-1}$ and a_t is stationary. As in the Blanchard and Watson [3] explosive bubble, investor overreaction is reflected if, say, $\pi = 1/2$ and the fad "bursts" if there is bad news about fundamentals.

In one interpretation, fads mean that even after risk adjustments there are profitable opportunities, at least for smart investors with long enough horizons. This apparently is the conclusion of some readers of Shiller [40] (e.g., Ackley [2]).

Another interpretation is that while some fraction of trading is done by naive traders, another fraction of trading is done by sophisticated investors who ensure that there are no extraordinary expected returns once risk is properly accounted for (Campbell and Kyle [5], DeLong et al. [11]). This does not mean that stock prices are driven to whatever level they would be in the absence of fads. Risk is created by naive investors, which sophisticated investors must take into account. Such risk might not, however, be captured by traditional models. See especially DeLong et al. [11], which contains a highly stylized model in which nondiversifiable risk created by noise trading causes the prices of two seemingly identical assets to diverge.[14]

There is of course much anecdotal evidence of fads, including the famous beauty-contest passage in Keynes [22]. More formal evidence consistent with stories of investor overreaction may be found in DeBondt and Thaler [9, 10] and Lehmann [26]. These papers find that abnormally high returns can be earned by following a contrarian strategy of buying stocks that recently have had relatively poor returns and shorting stocks that recently have performed well.[15] See DeLong et al. [11] and Camerer [4] for additional examples.

At a more aggregative level, a growing number of studies suggest that there is a significant stationary component to stock prices (Lo and McKinley [29], Fama and French [15], Poterba and Summers [39]). This component (a_t in equation (12)) is associated with econometric predictability of stock returns, using variables such as lagged dividend/price ratios or earnings. The predictability is particularly marked at long horizons, say, over two years (Campbell and Shiller [8], Fama and French [14, 15], Flood et al. [18]).

Poterba and Summers [39] and Shiller [43] interpret this as evidence of slowly mean-reverting fads. But the only unambiguous interpretation of evidence that stock prices do not follow a random walk is that expected returns are time varying. Whether or not the studies just cited imply movements in expected returns that can best be explained by fads is debatable (Fama and French [14]); one can trivially define a_t in equation (12) as simply the log of the ratio of the

[14] It should be noted that in this interpretation of fads, many of the traditional tools of financial analysis are still applicable, with the presence of noise trading an additional constraint facing rational investors. It therefore seems extreme to conclude (Kleidon [24], Merton [36]) that we can allow for fads only by ignoring much of our accumulated knowledge about financial markets. See Shiller [44].

[15] Whether these seeming pricing anomalies reflect not idiosyncratic risk but mismeasured nondiversifiable risk is, however, unclear.

stock price (15), with returns determined by some standard model, to a constant-expected-return price. So evidence of a stationary component is at best suggestive of fads. This applies as well to Campbell and Kyle [5], a fully articulated empirical study that allows for fads. It estimates an explicit model of trading by sophisticated investors, when a residual noise process affects stock prices. It finds that the noise process accounts for over one fourth of stock price movements in the S&P data, 1871–1984, but does not present any evidence that this process results mainly from trading by naive investors.

Traditional present-value models (e.g., those discussed in Section IV) are well enough specified that one can potentially argue that these models cannot adequately explain stock price volatility. I do not believe that the same can be said for fads models that have been developed so far. The quantitative evidence in favor of fads as an explanation of stock price volatility is largely indirect, in the form of negative verdicts on bubbles and on traditional models for returns.

More direct evidence on fads, and tests of restrictions implied by fads, may well be forthcoming shortly. But at present there is little formal positive evidence to sway someone unsympathetic to fads models.

Appendix

This gives detailed sources for Tables I and III. Notation matches that in the cited paper.

Table I: Line (1): Blanchard and Watson [3] (p. 18), V/V^* = ratio of $\hat{V}_c$ to $\hat{V}_c^{\max}$. *Line (2)*: Kleidon [25] (p. 983), Table 2, case (ii); p-value computed from "No. of Gross Violations" column. *Line (3)*: Leroy and Porter [28] (p. 572), Table III, $V/V^* = \gamma_y(0)/\gamma_y^*(0)$; p-value is that associated with f_2^u. *Line (4)*: Shiller [40] (p. 431), Table 2, V/V^* = square of ratio of line (5) to line (6). *Line (5)*: Shiller [45] (p. 7), Table 1, Case C; p-value computed from column (2). *Line (6)*: Campbell and Shiller [6] (p. 1078), Table 3, panel B, $V/V^* = \text{var}(SL)/\text{var}(SL')$ and $\text{var}(\xi)/\text{var}(\xi')$. *Line (7)*: Mankiw et al. [32] (pp. 685, 688), Tables I and II, V/V^* = ratio of $\text{E}(P - P^0)^2$ to $\text{E}(P^* - P^0)^2$. *Line (8)*: West [53], Table II, $V/V^* = [1 - (.01 \times \text{col}(8))]^{-1}$, for differenced specifications, with p-value in col. (7); Monte Carlo results are from Tables IIIA and IIIB. *Line (9)*: Campbell and Shiller [7] (p. 40), Table 4b, $V/V^* = [\sigma(\delta_t')/\sigma(\delta_t)]^{-2}$, with p-value for H_0: $\sigma(\delta_t')/\sigma(\delta_t) = 1$. *Line (10)*: Kleidon [25] (p. 986), Table 3, V/V^* = square of "Standard and Poor's Ratio" column; p-value computed from "Number of Simulation Violations > 1" column. *Line (11)*: Leroy and Parke [27] (p. 22), V/V^* = square of reported ratio of standard deviations. *Line (12)*: Shiller [42] (p. 237).

Table III: Line (1): Constant premium: Campbell and Shiller [7] (p. 41), Table 5, $V/V^* = [\sigma(\delta_t')/\sigma(\delta_t)]^{-2}$, with p-value for H_0: $\sigma(\delta_t')/\sigma(\delta_t) = 1$. Consumption and return volatility: $V/V^* = [\sigma(\delta_t')/\sigma(\delta_t)]^{-2}$, with p-value for H_0: $\sigma(\delta_t')/\sigma(\delta_t) = 1$; these figures are not reported in the paper but were given to me by John Campbell. *Line (2)*: West [53], Table IVA, $V/V^* = [1 - (.01 \times \text{percentage excess variability})]^{-1}$ for $\alpha \le 2$.

REFERENCES

1. Andrew Abel, N. Gregory Mankiw, Lawrence H. Summers, and Richard J. Zeckhauser. "Assessing Dynamic Efficiency: Theory and Evidence." NBER Working Paper No. 2097, December 1986.
2. Gardner Ackley. "Commodities and Capital: Prices and Quantities." *American Economic Review* 73 (March 1983), 1–16.
3. Olivier J. Blanchard and Mark Watson. "Bubbles, Rational Expectations and Financial Markets." NBER Working Paper No. 945, 1982.
4. Colin Camerer. "Bubbles and Fads in Asset Prices: A Review of Theory and Evidence." Manuscript, University of Pennsylvania, 1987.
5. John Y. Campbell and Albert S. Kyle. "Smart Money, Noise Trading and Stock Price Behavior." Manuscript, Princeton University, September 1986.
6. John Y. Campbell and Robert J. Shiller. "Cointegration and Tests of Present Value Models." *Journal of Political Economy* 95 (October 1987), 1062–88.
7. ———. "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors." Manuscript, Princeton University, October 1987.
8. ———. "Stock Prices, Earnings and Expected Dividends." Manuscript, Princeton University, December 1987.
9. Werner F. M. DeBondt and Richard Thaler. "Does the Stock Market Overreact?" *Journal of Finance* 40 (July 1985), 793–808.
10. ———. "Further Evidence on Investor Overreaction and Stock Market Seasonality." *Journal of Finance* 42 (July 1987), 557–81.
11. J. Bradford DeLong, Andrei Schliefer, Lawrence H. Summers, and Robert J. Waldmann. "The Economic Consequences of Noise Traders." Manuscript, Harvard University, September 1987.
12. Behzad T. Diba and Herschel I. Grossman. "On the Inception of Rational Bubbles." *Quarterly Journal of Economics* (August 1987), 697–700.
13. Robert F. Engle and C. W. J. Granger. "Dynamic Model Specification with Equilibrium Constraints: Co-Integration and Error Correction." *Econometrica* (March 1987), 251–76.
14. Eugene F. Fama and Kenneth R. French. "Dividend Yields and Expected Stock Returns." Manuscript, University of Chicago, November 1987.
15. ———. "Permanent and Transitory Components of Stock Prices." *Journal of Political Economy* (April 1988), forthcoming.
16. Marjorie Flavin. "Excess Volatility in the Financial Markets: A Reassessment of the Empirical Evidence." *Journal of Political Economy* (October 1983), 929–56.
17. Robert P. Flood and Robert J. Hodrick. "Asset Price Volatility, Bubbles and Process Switching." *Journal of Finance* 41 (September 1986), 831–42.
18. ———, and Paul Kaplan. "An Evaluation of Recent Evidence on Stock Market Bubbles." Manuscript, Northwestern University, 1986.
19. Christian Gilles and Stephen F. Leroy. "Bubbles and Charges." Manuscript, University of California at Santa Barbara, November 1987.
20. ———. "The Variance Bounds Tests: A Critical Survey." Manuscript, University of California at Santa Barbara, August 1987.
21. Robert J. Gordon. *Macroeconomics.* Boston: Little, Brown and Company, 1987.
22. John M. Keynes. *The General Theory of Employment, Interest and Money.* New York: Harcourt, Brace and World, 1964.
23. Allan W. Kleidon. "Bias in Small Sample Tests of Stock Price Rationality." Stanford University Graduate School of Business Research Paper 819R, September 1985.
24. ———. "Anomalies in Financial Economics: Blueprint for Change?" *Journal of Business* 59 (October 1986), S469–S499.
25. ———. "Variance Bounds Tests and Stock Price Valuation Models." *Journal of Political Economy* (October 1986), 953–1001.
26. Bruce Lehmann. "Fads, Martingales and Market Efficiency." Manuscript, Columbia University, May 1987.
27. Stephen F. LeRoy and William R. Parke. "Stock Price Volatility: A Test Based on the Geometric Random Walk." Manuscript, University of California at Santa Barbara, August 1987.
28. Stephen F. LeRoy and Richard Porter. "The Present Value Relation: Tests Based on Implied

Variance Bounds." *Econometrica* 49 (May 1981), 555–674.
29. Andrew W. Lo and A. Craig McKinley. "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test." Manuscript, University of Pennsylvania, 1987.
30. John B. Long, Jr. "Discussion." *Journal of Finance* 36 (July 1981), 304–7.
31. Robert E. Lucas, Jr. "Asset Prices in an Exchange Economy." *Econometrica* 46 (November 1978), 1429–45.
32. N. Gregory Mankiw, David Romer, and Matthew D. Shapiro. "An Unbiased Reexamination of Stock Price Volatility." *Journal of Finance* 40 (July 1985), 677–88.
33. Terry A. Marsh and Robert C. Merton. "Dividend Variability and Variance Bounds Tests for the Rationality of Stock Market Prices." *American Economic Review* 76 (June 1986), 1429–45.
34. ———. "Dividend Behavior for the Aggregate Stock Market." *Journal of Business* 60 (January 1987), 1–40.
35. Joe Mattey and Richard Meese. "Empirical Assessment of Present Value Relations." *Econometric Reviews* 5 (1986), 171–234.
36. Robert C. Merton. "On the Current State of the Stock Market Rationality Hypothesis." Sloan School of Management Working Paper No. 1712-85, 1985.
37. James O'Brien. "Speculative Bubbles and the Need for Stock Margin Requirements." Manuscript, Federal Reserve Board of Governors, November 1984.
38. Maurice Obstfeld and Kenneth Rogoff. "Ruling Out Divergent Speculative Bubbles." *Journal of Monetary Economics* 17 (May 1986), 349–62.
39. James M. Poterba and Lawrence H. Summers. "Mean Reversion in Stock Prices: Evidence and Implications." NBER Working Paper No. 2343, August 1987.
40. Robert J. Shiller. "Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?" *American Economic Review* 71 (June 1981), 421–36.
41. ———. "The Use of Volatility Measures in Assessing Market Efficiency." *Journal of Finance* 35 (May 1981), 421–36.
42. ———. "Reply." *American Economic Review* (March 1983), 236–37.
43. ———. "Stock Prices and Social Dynamics." *Brookings Papers on Economic Activity* (1984), 457–98.
44. ———. "Comments on Miller and Kleidon." *Journal of Business* 59 (October 1986), S501–S505.
45. ———. "The Probability of Gross Violations of a Present Value Variance Inequality." Manuscript, Yale University, July 1986.
46. Kenneth J. Singleton. "Expectations of the Term Structure and Implied Variance Bounds." *Journal of Political Economy* (December 1980), 159–76.
47. Gregor W. Smith. "Apparent Bubbles and Misspecified Fundamentals." Queens University Institute for Economic Research Working Paper No. 692, 1987.
48. Lawrence H. Summers. "Does the Stock Market Rationally Reflect Fundamental Values?" *Journal of Finance* 41 (July 1986), 591–601.
49. Jean Tirole. "On the Possibility of Speculation Under Rational Expectations." *Econometrica* 50 (September 1982), 1163–81.
50. ———. "Asset Bubbles and Overlapping Generations." *Econometrica* 53 (September 1986), 1071–1100.
51. Kenneth D. West. "Comment." *Econometric Reviews* 5 (1986), 273–78.
52. ———. "A Specification Test for Speculative Bubbles." *Quarterly Journal of Economics* (August 1987), 553–80.
53. ———. "Dividend Innovations and Stock Price Volatility." *Econometrica* 56 (January 1988), 37–61.

DISCUSSION

ALLAN W. KLEIDON*: Suppose that, seven years ago, research was reported showing that expected returns on stocks were not constant, and that consequently the results of tests that assumed constant expected returns showed apparent violation of (otherwise) rational valuation models. What would have been the

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